Agricultural Productivity Growth and Deforestation in the Tropics*

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Abstract

We analyze the impact of agricultural productivity growth on tropical deforestation. Our dynamic model of forest-to-farmland conversion incorporates costs and market constraints on agricultural output, emphasizing that productivity growth, rather than its absolute level, shapes deforestation patterns. Addressing the Jevons' paradox and Borlaug hypothesis, the model predicts that rising agricultural productivity, reflected by declining fertilizer price growth, has an ambiguous effect on deforestation. Using tropical forest loss data (2000-2022) and fertilizer price variations, we find a negative correlation between fertilizer price growth and deforestation, particularly in regions with high market potential. Without the 10% annual rise in fertilizer prices over the period, deforestation rates would have been 57% faster, representing 6.6 million additional hectares annually. Conversely, the 3% annual increase in crop prices has a minimal impact on deforestation. Our results highlight that protected areas do not mitigate the adverse effects of fertilizer price growth on deforestation.

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1 Introduction

Halting tropical deforestation has been a prominent global policy objective for over three decades. Yet, global deforestation in 2022 was 20% higher than at the turn of the 21st century.[1] This increase in deforestation has been driven by the expansion of agricultural lands (Branthomme et al., 2023). With projections indicating a 30% increase in global food demand by 2050 (Fukase & Martin, 2020), the pressure on forests will intensify in the coming decades.

One potential strategy for curbing deforestation without compromising agricultural output, known as Borlaug's hypothesis, involves promoting technologies that improve agricultural productivity such as fertilizers (Borlaug, 2007; Phalan et al., 2011). These technologies allow farmers to increase yields on their existing lands, potentially sparing forests from conversion to agriculture. However, increasing yields also raises the opportunity costs of protecting remaining forests, leading to a potential increase in deforestation through a rebound effect (Kremen & Merenlender, 2018; Rudel et al., 2009). Both general equilibrium effects[2] and policy interventions, such as the creation of protected areas, could mitigate this rebound effect. Early discussions in the literature have acknowledged the ambiguous theoretical predictions (Angelsen & Kaimowitz, 1999; Balboni et al., 2023), and empirical results diverge (Abman & Carney, 2020; Hess et al., 2021).

In this article, we start by presenting a theoretical model of agricultural production that clarifies how agricultural productivity affects deforestation over time. We derive three theoretical predictions from this model that we empirically test in the second part of the paper. In particular, we focus on the dynamic decision of a farmer to clear forest to expand their agricultural land. Agricultural production in a given season depends on cumulative deforestation over the previous seasons, and agricultural productivity depends on the amount of fertilizer used during the current season. Solving the model reveals that the growth in agricultural productivity, rather than the absolute level of agricultural productivity itself, influences deforestation rates. It also leads us to our first theoretical prediction which is that the overall relationship between fertilizer price growth and deforestation is ambiguous.

Farmers across the tropics face varying levels of demand for their agricultural outputs, influenced by their proximity to densely populated areas (such as the Great Lakes region in Central Africa or across East Asia) or by their remoteness (like the Congo Basin or the State of Acre in northern Brazil). Consequently, the ability of farmers to sell their output might be constrained by their market potential.[3] We show that the impact of fertilizer price growth on deforestation is negative when the farmer does not reach their market potential and positive when they do. As output and fertilizer prices vary from season to season, farmer's production may be limited by market potential in some seasons and not in others. This leads to our second prediction: the impact of fertilizer price growth is larger in regions with lower market potential compared to areas with higher market potential.

[1] The data from the Global Forest Initiative used in this paper, available at: https://research.wri.org/gfr/latest-analysis-deforestation-trends, supports this.

[2] See (Hertel et al., 2014; Stevenson et al., 2013; Villoria, 2019).

[3] Market potential is defined as the maximum quantity of product they can sell within each period and is measured by nightlight intensity inversely weighted by geographical distance.

Our model finally incorporates environmental policies to explore whether existing ones can be effective at protecting forests against increases in agricultural productivity. More particularly, our model considers two types of forests: protected and unprotected ones. Drawing from the law and economics literature, we assume that enforcement of protected areas is imperfect and primarily operates through fines (Becker, 1968). Our third prediction is that the presence of protected areas in our dynamic setting does not alter the relationship between fertilizer price growth and deforestation.

Next, we test these three theoretical predictions using tree cover loss data covering 22 years and the entire tropics. We combine tree cover loss and soil characteristics data with global fluctuations in fertilizer prices to identify local exogenous shifts in fertilizer prices between 2000 and 2022 at a spatial resolution of 0.5 degrees $\times$ 0.5 degrees ($\approx$ 55km$\times$55km at the equator). Our empirical results reveal a negative correlation between fertilizer price growth and tree cover loss at a global scale. This implies that areas where agricultural productivity decreased over the past 22 years have experienced lower deforestation rates than in areas where agricultural productivity increased. The effect of fertilizers prices is substantial. It exceeds by ten times the effect of output price growth. During the study period, fertilizer prices rose by approximately 10% annually, while output prices increased by 3% annually. Without the observed increases in fertilizer prices, we estimate that the deforestation rate would have been 57% higher. Conversely, without the increases in output prices, the deforestation rate would have been only 3% lower.

Furthermore, consistent with our second theoretical prediction, we find that the negative correlation between fertilizers price growth and deforestation is stronger in areas with high market potential. In addition, we observe a similar negative effect across both protected and unprotected lands. Finally, we control in some specifications for both the price growth of fertilizers and the agricultural output to account for general equilibrium adjustments. When doing so, the negative effect of fertilizer price growth on deforestation remains unchanged.

Contribution. Our study makes several contributions to the economic literature on deforestation. Firstly, our model highlights the importance of ensuring consistency between the measures used on the right-hand side (prices, quantities, productivity) and those on the left-hand side (forest cover, forest loss, or deforestation rate). If the left-hand side variable is measured in levels (such as forest cover), the right-hand side variables must also be measured in levels. Likewise, if the left-hand side variable is measured in changes (such as deforestation), the right-hand side variables must also be measured in changes. Yet, it is common in the literature to explain deforestation (a change) by using right-hand side variables in levels (Abman & Carney, 2020; Assunção et al., 2023; Berman et al., 2023; Bernard et al., 2023; Carreira et al., 2023; Cisneros et al., 2021; Harding et al., 2021; Hess et al., 2021; Kassouri, 2024). Our model underscores that such specification fails to account for the fact that agricultural production can utilize land that has been deforested in the past, not just the land cleared in the current season.

Secondly, while deforestation and agricultural expansion are intrinsically dynamic phenomena, most theoretical models in the literature are static (Angelsen, 1999; Chomitz & Gray, 1996; Dominguez-Iino, 2023; Souza-Rodrigues, 2019) or focus on the steady state without deforestation (López, 1997). An important exception is Harstad (forth.),[4] who examines the effects of trade between two entities—the

[4] Another exception is Farrokhi et al. (2024) who consider a dynamic model of trade and deforestation and focus on the

South and the North—both possessing market power, on these dynamic phenomena. However, our objective here is to investigate deforestation at a local level. Therefore, we concentrate on the actions of price-taking farmers who determine the rate at which they convert forests into farmland, in response to productivity shocks, such as variations in fertilizer prices.

Thirdly, existing empirical tests of the Borlaug vs Jevons hypotheses for deforestation have been conducted at the scale of countries. Our dataset encompasses the entire tropics, thereby enhancing the external validity of our findings.

Fourthly, several empirical studies demonstrate that expanding market access correlates with increased deforestation, including in Ghana (Abman & Lundberg, 2024), Brazil (Souza-Rodrigues, 2019), the D.R Congo (Damania et al., 2018) or when focusing on the impact of ratifying a regional trade agreement (Abman & Lundberg, 2020). Our results on market potential point in the same direction, showing that higher market potential amplifies the impact of fertilizer price growth on deforestation.

Finally, a substantial body of literature in conservation science shows that protected areas in the tropics have only limited effectiveness in reducing deforestation (Geldmann et al., 2019; Lindsey et al., 2018; Meng et al., 2023), especially when farmers face adverse economic conditions (Desbureaux & Damania, 2018). Our analysis contributes to this literature by theoretically and empirically illustrating that existing protected areas do not attenuate the impact of agricultural productivity growth on deforestation.

In the following Section 2, we present our dynamic model of agricultural production and deforestation. Section 3 describes the data, the methodology used to construct our main variables of interest, and our econometric approach. Section 4 contains the baseline results, a number of sensitivity analyses and investigations of the role of market potential and protected areas. The last section concludes.

2 The Model

2.1 Assumptions

We consider a farmer who produces a quantity of crop y using two inputs: agricultural lands l_t and fertilizers f_t. We assume a Cobb-Douglas production function, $y(l, f) = l^{\alpha} f^{\gamma}$, with $\alpha + \gamma < 1$[5] and $\alpha, \gamma \geq 0$. The farmer is price-taker and sells their output at price p_t^o. The unit cost of farming surface l_t is c_l and the unit price of fertilizer at time t is p_t^f. The total land surface that can be cultivated at time t, thereafter agricultural land, is a stock A_t. This stock can be increased by converting forests to farmlands at unit cost $c_a \in \{\underline{c}_a, \overline{c}_a\}$. This cost is low ($c_a = \underline{c}_a$) if the converted forest is outside protected areas, and is high ($c_a = \overline{c}_a > \underline{c}_a$) if the forest belongs to a protected area since it includes the expected fines imposed for the violation of protected areas.

The dynamics of agricultural land accumulation are $A_t = A_{t-1} + a_t$, where a_t represents the newly converted land at time t. Land can only be cultivated if it has been converted into agricultural land.

effect of unilateral versus multilateral changes in trade costs on deforestation at the steady state.

[5]The Cobb-Douglas function is the standard functional form for agricultural production (Chamberlin & Ricker-Gilbert, 2016; Griliches, 1964; Hayami, 1970).

However, farmers are not obligated to cultivate all their agricultural lands, implying that the cultivated area land must be less than or equal to the total agricultural land, $l_t \leq A_t$.

Since not all deforested land is exclusively used for agricultural purposes but also for infrastructure such as roads, residential buildings for families and workers, and machinery, we introduce $\epsilon \geq 0$ as the elasticity of forest conversion to agricultural land. This parameter signifies that to increase agricultural land by 1%, forest cover must decrease by ϵ%. Denoting F_t as the forested area, we relate it to the agricultural land A_t as $F_t = \frac{1}{\epsilon} A_t^{-\epsilon}$.

Additionally, we assume that farmer cannot store their output and face a market potential limit $\bar{y}$. This limit is defined as the maximum quantity of production the farmer can sell in each period, constrained by transportation costs and the market sizes accessible via the transportation network.

The farmer aims to maximize their expected discounted profits with discount factor $\delta \in [0, 1[$, and thus solves the following optimization program:

$$\max_{a_t, l_t, f_t \geq 0} \sum_{0}^{+\infty} \delta^t \pi_t, \tag{1}$$

where $\pi_t = p_t^o y(l_t, f_t) - c_a a_t - c_l l_t - p_t^f f_t$, given the dynamics of agricultural land $A_t = A_{t-1} + a_t$, the agricultural land constraint $l_t \leq A_t$ and the market potential constraint $y(l_t, f_t) \leq \bar{y}$.

2.2 Theoretical results

The Lagrangian for the optimization problem of the farmer is:

$$L = \sum_{t=0}^{+\infty} \left(\delta^t \pi_t + \lambda_t \left(a_t + A_{t-1} - A_t \right) + \mu_t^A \left(A_t - l_t \right) + \mu_t^y \left(\bar{y} - y(l_t, f_t) \right) + \mu_t^a a_t + \mu_t^l y_t + \mu_t^f f_t \right), \tag{2}$$

where λ_t is the co-state variable associated with the stock A_t, and, the μs are the multipliers associated with the non-negativity constraints $A_t - l_t \geq 0$, and $\bar{y} - y(l_t, f_t) \geq 0$, $a_t \geq 0$, $l_t \geq 0$ and $f_t \geq 0$.

Assuming that the farmer clears some land and produces some output $(l_t, f_t, a_t > 0)$, we must have $\mu_t^a = \mu_t^l = \mu_t^f = 0$ and the following necessary conditions hold:

$$\frac{\partial L}{\partial a_t} = -\delta^t c_a + \lambda_t = 0, \tag{3}$$

$$\frac{\partial L}{\partial l_t} = \left(\delta^t p_t^o - \mu_t^y \right) y_l(l_t, f_t) - c_l - \mu_t^A = 0, \tag{4}$$

$$\frac{\partial L}{\partial f_t} = \left(\delta^t p_t^o - \mu_t^y \right) y_f(l_t, f_t) - p_t^f = 0, \tag{5}$$

$$\frac{\partial L}{\partial A_t} = \lambda_{t+1} - \lambda_t + \mu_t^A = 0, \tag{6}$$

$$\mu_t^A \left(A_t - l_t \right) = 0, \tag{7}$$

$$\mu_t^y \left(\bar{y} - y(l_t, f_t) \right) = 0, \tag{8}$$

$$\mu_t^A, (A_t - l_t), \mu_t^y (\bar{y} - y(l_t, f_t)) \geq 0, \tag{9}$$

where y_x denotes the derivative of y with respect to $x = l, f$.

Condition (3) asserts that the marginal cost of land conversion must equal the shadow price of agricultural land. Condition (4) pertains to the choice of the cultivated land area, stating that the marginal increase in profits equals the marginal increase in the opportunity cost,which includes the marginal cost of farming k, the scarcity of agricultural land (μ_t^A), and the market-induced demand scarcity ($\mu_t^y y_l$). Condition (5) concerns fertilizer use, requiring that the marginal increase in profits equals the fertilizer price p_t^f. The remaining conditions account for whether the agricultural land constraint and the market potential constraint are saturated or not. Condition (6) (coupled with (9)) states that the evolution of the shadow price of agricultural land must equal its marginal value to the farmer (μ_t^A).

Note that condition (3) implies $\lambda_{t+1} - \lambda_t = \delta^t (\delta - 1) c < 0$. Therefore, the shadow price of agricultural land is strictly decreasing over time. Combined with condition (9), this indicates that the farmer has an incentive to farm all available agricultural lands, i.e., $l_t^* = A_t^*$.

To simplify our equations, we introduce the following notations: $D_t = -\ln(1 - r_t)$ represents our measure of deforestation, where $r_t = \frac{F_{t-1} - F_t}{F_{t-1}}$ denotes the deforestation rate, $g_t^f = \frac{p_t^f - p_{t-1}^f}{p_{t-1}^f}$ signifies the the growth rate of fertilizer prices, and $g_t^o = \frac{p_t^o - p_{t-1}^o}{p_{t-1}^o}$ represents the growth rate of output prices.

The problem can then be solved by distinguishing two cases, based on whether the market potential is saturated or not. Let us consider these cases separately:

Case 1: Non binding market potential ($y(l_t, f_t) < \bar{y}$): In this case, we must have $\mu_t^y = 0$. After some simple computations, one can solve for the optimum.[6] The optimal cultivated land surface is given by:

$$l_t^* = A_t^* = e^{\Phi_t} (p_t^o)^{\frac{1}{1-\alpha-\gamma}} \left(p_t^f\right)^{\frac{-\gamma}{1-\alpha-\gamma}}, \tag{10}$$

where $\Phi_t = \frac{1-\gamma}{1-\alpha-\gamma} \ln \left(\frac{\alpha(1-\alpha)^{\frac{\gamma}{1-\gamma}} (\delta^t)^{\frac{1}{1-\gamma}}}{c_l + (1-\delta) c_a \delta^{t-1}} \right)$.

We can rewrite this condition in terms of deforestation rate as follows:

$$-\ln(1 - r_t) = \beta_1 \ln\left(1 + g_t^f\right) + \beta_2 \ln(1 + g_t^o) + \nu_t, \tag{11}$$

where $\beta_1 = -\frac{\epsilon\gamma}{1-\alpha-\gamma} < 0$, $\beta_2 = \frac{\epsilon}{1-\alpha-\gamma} > 0$, and $\nu_t = \frac{\ln(\delta)}{1-\alpha-\gamma} + \frac{1-\gamma}{1-\alpha-\gamma} \ln \left(\frac{c_l + c_a(1-\delta)\delta^{t-2}}{c_l + c_a(1-\delta)\delta^{t-1}} \right)$.

The left hand side in equation (11) represents an index of deforestation that rises with increasing deforestation rates. This equation illustrates that higher growth in fertilizer prices correlates with lower levels of deforestation. Moreover, deforestation diminishes with increases in the costs associated with land conversion c_a or farming c_l.

[6] The optimal level of fertilizer use is given by $\frac{f_t^*}{A_t^*} = \frac{1-\alpha}{\alpha} \frac{c_l + \delta^{t-1} c_a (1-\delta)}{p_t^f}$.

Case 2: Binding market potential ($\mu_t^y > 0 => y(l_t, f_t) = \bar{y}$): In this case, using $y(l_t^*, f_t^*) = \bar{y}$ and $l_t^* = A_t^*$, we directly find the optimal surface of farmed land:[7]

$$l_t^* = A_t^* = \bar{y}^{\frac{1}{\alpha+\gamma}} \left(\frac{\alpha}{\gamma} \frac{p_t^f}{c_l} \right)^{\frac{\gamma}{\alpha+\gamma}} \tag{12}$$

We can again rewrite this condition in terms of deforestation rate:

$$-\ln(1 - r_t) = \beta_1 \ln \left(1 + g_t^f \right), \tag{13}$$

where $\beta_1 = \frac{\epsilon\gamma}{1-\alpha-\gamma} > 0$.

This condition suggests a reversal compared to the scenario where the market potential is not binding: higher growth in fertilizer prices leads to increased deforestation levels. Additionally, in this case, the level of deforestation is independent of the output price p_t^o, the cost of converting land c_a, or on the cost of farming c_l.

We can compute the optimal value of the multiplier associated with the market potential constraint and we obtain $\mu_t^y = \rho_t \left(\frac{(p_t^o)^{\alpha+\gamma}}{(p_t^f)^{\gamma}} \right)^{\frac{1}{1-\alpha-\gamma}}$, where $\rho_t = \frac{\delta^t \gamma^{\frac{\gamma}{\gamma+\alpha}}}{c_l^{\frac{\alpha}{\alpha+\gamma}} \alpha^{1-\gamma+\gamma\frac{1-\alpha-\gamma}{\alpha+\gamma}}}$. Let G be the cumulative distribution of μ_t^y. Thus $G(\bar{y})$ is the probability that the market potential constraint is not binding. Using this notation, we can compute the expectation of our parameter of interest, β_1:

$$E[\beta_1] = G(\bar{y}) \frac{-\epsilon}{1-\alpha-\gamma} + (1 - G(\bar{y})) \frac{\epsilon}{1-\alpha-\gamma} = (1 - 2G(\bar{y}) \frac{\epsilon}{1-\alpha-\gamma}. \tag{14}$$

This expression carries three notable implications: i) the expected effect of fertilizer price growth on deforestation ($E[\beta_1]$) can be either positive or negative, ii) $E[\beta_1]$ decreases as market potential increases, and iii) it remains independent of clearing cost c_a. These implications allows us to formulate three testable predictions based on the model.

2.3 Predictions

We derive three testable predictions from equation (14):

Prediction 1 [agricultural productivity growth and deforestation]: *The link between fertilizer price growth and the deforestation rate is ambiguous,* $\frac{\partial r_t}{\partial g_t^f} \lesseqgtr 0$.

Thus, determining whether the effect is positive or negative is an empirical question. Indeed, market potential can be binding at certain periods and not at others, particularly in areas with low market potential. Therefore, the following prediction can be inferred:

[7] The optimal use of fertilizer is given by $\frac{f_t^*}{A_t^*} = \frac{\gamma}{\alpha} \frac{c_l}{p_t^f}$

Prediction 2 [market potential]: *The effect of increased fertilizer price growth on the deforestation rate is more pronounced in areas with lower market potential compared to those with higher market potential,* $\bar{y}_1 > \bar{y}_2 \implies \frac{\partial r_t}{\partial g_t^f}|_{\bar{y}=\bar{y}_2} > \frac{\partial r_t}{\partial g_t^f}|_{\bar{y}=\bar{y}_1}$.

As discussed above, our framework also explores the effect of protected areas by assuming that they increase increase the cost of land clearance. Based on this assumption, we derive the following prediction.

Prediction 3 [protected areas]: *Existing protected areas do not affect the relationship between the deforestation rate and the growth of fertilizer prices,* $\frac{\partial r_t}{\partial g_t^f}|_{c_a=\bar{c}_a} = \frac{\partial r_t}{\partial g_t^f}|_{c_a=\underline{c}_a}$

Therefore, protected areas are unable to mitigate forest loss resulting from fluctuations in fertilizer price growth (see equation (11) and (13)).

3 Data and Empirical Strategy

We consider a full set of grid cells for the tropics, i.e. the area between the Tropics of Cancer at 23°26' N and Capricorn at 23°26' S, divided in sub-national units of 0.5 $\times$ 0.5 degrees latitude and longitude ($\approx$ 55 $\times$ 55 kilometers at the equator). The unit of observation in our dataset is a cell-year between 2001 and 2022 period.

3.1 Data

Deforestation. We use annual tree cover loss data from Hansen et al. (2013) (version v1.10).[8] The data provide an estimation of tree cover density in 2000 at a 1 arc-second (around 30 meters) scale. For each subsequent year, the data indicate if trees in a pixel were cleared or not. In our baseline estimates, we follow other global studies and consider a 1 arc-second pixel as being a forest when initial tree cover in 2000 is larger than 25% (Hansen et al., 2010; Heino et al., 2015; Potapov et al., 2008). We estimate the sensitivity of our results to a 10% or to a 50% canopy thresholds in Section 4.4.

We use Zvoleff (2020)'s package to aggregate data from a 1 arc second at the 0.5-degrees grid cell level, and we compute the area of tree cover in 2000 and the yearly area deforested, from 2001 to 2022 (all in hectares). This aggregation from 1 arc-second to the 0.5-degrees scale limits the issue of non-classical measurement errors - a known problem in the Hansen dataset (Alix-Garcia & Millimet, 2023),[9] and allows to use the Hansen dataset in a panel setting (Garcia & Heilmayr, 2024). With this data, and prompted by our model (equations 11 and 13), our dependent variable, the time-varying cell-specific index of deforestation is: $\text{Deforest}_{it} = -\ln(1 - r_{it})$, where $r_{it} = \text{loss}_{it}/\text{cover}_{it}$ is the deforestation rate, loss_{it} is forest loss, and cover_{it} is forest cover at the beginning of year t.

[8] See https://www.globalforestwatch.org.

[9] Each 0.5-degrees grid cells contains approximately 4 millions 1 arc-second pixels.

Fertilizer Price Index. As there are no local fertilizer price data with sufficient spatial granularity from 2001 to 2022, and because local fertilizer prices would likely be endogenous to local deforestation, we approximate fertilizers price as in Berman et al. (2021). The intuition is that different cells are suitable for different crops, and the fertilizer content required for each crops varies. Fertilizers typically contain a mix of nitrogen, phosphate and potassium (N-P-K). This mix varies across different types of fertilizers to meet crop-specific needs. By combining data on local crop suitability with the international market price of each fertilizer component, we construct a fertilizer price that varies across locations and over time. More precisely, we combine three types of data: (i) data on crop suitability from FAO's Global Agro-Ecological Zones (GAEZ)[10]; (ii) information on crop-specific nutrients uptakes from the International Plant Nutrient Institute (IPNI), measured in kg/ha (Table A 4, Appendix Section B); and (iii) data on the annual price of each nutrient from the World Bank Commodities Dataset.[11]

GAEZ data is constructed from models that use location characteristics such as climate information (as rainfall and temperature), soil characteristics and crop characteristics to estimate the suitability of crops by pixels of 0.08°×0.08°. The primary advantage of this data lies in its ability to isolate crop suitability from deforestation, as it does not rely on actual crop production.

We focus on 27 crops for which data on crop nutrients specific needs and agronomic suitability are available.[12] We compute the cell-specific *relative* suitability of the crop c in cell i (γ_{ic}) by dividing the suitability of the crop (S_{ic}) by the sum of the suitability of the crops in the cell i as follows:

$$s_{ic} = \frac{S_{ic}}{\sum_{j=1}^{27} S_{jc}}. \tag{15}$$

We then compute, for each cell, the international market price of a kilogram of local fertilizer based on the required N-P-K mix for each crop, weighted by its relative suitability in the cell :

$$p_{it}^{f} = \sum_{c} s_{ic} \left(P_t^N q_c^N + P_t^P q_c^P + P_t^K q_c^K \right), \tag{16}$$

where $\{P_t^N,\ P_t^P$, and $P_t^K\}$ represent the real international market prices of nitrogen, phosphate, and potassium respectively, and $\{q_c^N,\ q_c^P$, and $q_c^K\}$ are the required proportion (%) of the three nutrients for crop c, with $q_c^N + q_c^P + q_c^K = 1$. These proportions are computed from the quantities of nutrients that are removed from the soil at the time of harvest (in kg/ha), which is the quantity of each nutrient (in pounds) contained in 1 ton the crop. Prompted by our model (equations 11 and 13), we define our main explanatory variable, the (ln of one plus) fertilizer price growth, as follows: $\text{Fert. p. growth}_{it} = \ln\left(1 + g_{it}^f\right)$ where $g_{it}^f = (p_{it}^f - p_{it-1}^f)/p_{it-1}^f$ is the fertilizer price growth rate.

[10] GAEZ, FAO data, available http://www.fao.org/nr/gaez/about-data-portal/en/

[11] Figure A 3 in Appendix B displays nutrient prices growth over time. The three price spikes that occurred between 2008 and 2009 were due to a rise in demand triggered by US biofuel programs and the imposition of a 135% Chinese export tariff on phosphate (Schröder et al., 2010).

[12] The 27 crops are: barley, buckwheat, cabbage, chickpea, citrus, cow-pea, dry-pea, flax, maize, oat, millet, pigeon-pea, rape, reed, rice, rye, sorghum, soybean, sugar-cane, sugar-beet, sunflower, sweet-potato, switch-grass, tobacco, tomato, wheat, and white-potato.

Market Potential. For a given cell i, the market potential (MP_i) is computed as the sum of the nightlight intensity in 2000 of the other cells in the same continent weighted by the distance between the cells:[13]

$$MP_i = \sum_{z \neq i} \frac{n_z}{d_{iz}}, \tag{17}$$

Complementary data. Output price is a cell-specific price index computed as in Berman et al. (2023). It is a weighted sum of World Bank international crop prices (P^o_{ct}) with weights being the relative suitability of each crop (s_{ic}) from GAEZ:

$$p^o_{it} = \sum_c s_{ic} P^o_{ct}. \tag{18}$$

In line with our model, we use the growth rate of this variable as our measure of (the ln of one plus) output price growth, Output p. growth $= \ln(1 + g^o_{it})$ where $g^o_{it} = (p^o_{it} - p^o_{it-1})/p^o_{it-1}$ is the output price growth rate.

We also construct two weather variables, average annual temperature (in °C) and total annual precipitation (in mm), to account for local average conditions that might favor or limit deforestation. Our variables are derived from the interpolated data by Matsuura and Willmott (2015) which has been extensively used in economics (e.g.: Damania et al., 2020; Dell et al., 2012).

We use the World Database on Protected Areas (Bingham et al., 2019) to identify cells inside and outside protected areas.[14] We consider the year 2000 to avoid endogeneity concerns related to protected areas (see Amin et al., 2019). We use a dummy variable (Parks) which is set to 1 if any of the land in the cell is part of a protected area (this is the case for 53% of our sample).

We compute the average distance between the cells' centroids and the neareast ports and cities using data from Nelson et al. (2019). We consider cities categorized according to their number of inhabitants ([3k-5k[, [5k-50k[[50k-100k[, [100k-200k[, [200k-1 million[, [1 million - 5 million] and [5million and +]) and ports categorized according to their size (very small, small, medium and large).[15]

Final Sample. Our final sample covers the period 2001-2022 and is composed of 13,695 cells for which agronomic suitability data is available and forest cover in 2000 was strictly positive, i.e. at least 1 arc-second pixel is forest where the canopy threshold is larger than 25% of the cover. Our dataset is a balanced panel of 300,694 observations. Table 1 displays summary statistics about the main variables, including initial forest cover, deforestation and the price indexes.

Figure A 4 in Appendix B maps deforestation, fertilizer price growth, and their changes for each grid cell during the sample period. Panels A and B show yearly average deforestation and our fertilizer price growth index, respectively. The maps suggest a negative correlation between fertilizer price growth and deforestation. Panels C and D show annual variations in deforestation and our annual fertilizer price

[13]Nightlight data from the DMSP-OLS, Nighttime Lights Time Series Version 4 (Average Visible, Stable Lights, & Cloud Free Coverages), as available in PRIO-GRID, see .

[14]See https://www.protectedplanet.net/en/thematic-areas/wdpa?tab=WDPA

[15]Nelson et al. (2019) estimates are based on data for cities from Pesaresi and Freire (2016), and data for 3,700 ports locations and characteristics from National Geospatial-Intelligence Agency (2017).

Table 1: Summary Statistics

Variable	**Mean**	**Std. Dev.**	**N**
Deforest (-ln(1-r))	0.008	0.053	300694
Deforest rate (r)	0.007	0.029	300694
Fert. p. growth (ln(1+gf))	0.066	0.223	300694
Fert. p. growth (ln(1+go))	0.097	0.269	300694
Output p. growth (ln(1+go))	0.025	0.101	300694
Output p. g. rate (go)	0.03	0.105	300694
Fert. p. index (pf)	250.387	95.41	300694
Output p. index (po)	149.553	27.962	300694
Rainfall	1.67	0.887	292972
Temperature	19.714	3.512	292972
Market Pot.	8.478	1.12	300694
Parks	0.538	0.499	300694
Parks, cat 1 or 2	0.172	0.377	300694
Distance to ports (very small, ln)	6.363	1.019	300584
Distance to ports (small, ln)	6.489	0.947	300584
Distance to ports (medium, ln)	6.796	0.993	300584
Distance to ports (large, ln)	7.231	0.889	300584
Distance to cities (> 3k inhab., ln)	6.472	1.232	300628
Distance to cities (> 5k inhab., ln)	5.359	1.25	300628
Distance to cities (> 50k inhab., ln)	5.651	1.192	300628
Distance to cities (> 100k inhab., ln)	5.867	1.23	300628
Distance to cities (> 200k inhab., ln)	6.022	1.168	300628
Nightlights 2000 (ln)	3.687	3.788	300694

Note. Deforest is our index of deforestation computed as minus the log of one minus the deforestation rate (loss over forest cover), Deforest rate (r) is forest loss over forest cover, Fert. price growth is the log of one plus the current period fertilizer price growth rate, Fert. p. g. rate (g^f) is the growth rate of the price of fertilizers, Output price growth is the log of one plus the current period fertilizer price growth rate, and Output p. g. rate (g^o) is the growth rate of the price of the output. Prices data come from the World Bank Commodities Dataset, see https://databank.worldbank.org/databases/commodity-price-data. Rainfall and Temperature data come from the climate research unit from the University of East Anglia, see https://crudata.uea.ac.uk/cru/data/hrg/. Market potential is the log of night time lights intensity in 2000 weighted by the inverse of the distance between the cells. Dist. to cap. is the geodesic distance between each centroid grid cells and the capital city of each country. Dist to port. is the geodesic distance between each centroid grid cell of 0.5×0.5 degree longitude and latitude and the closest port, computed using the World Port Index dataset 18 that provides GPS location of ports with a depth larger than 11 meters, see https://msi.nga.mil/Publications/WPI. Nightlights 2000 is the log of night time lights intensity in 2000, data from the DMSP-OLS, Nighttime Lights Time Series Version 4 (Average Visible, Stable Lights, & Cloud Free Coverages), as available in PRIO-GRID, see . Protected area data come from the World Database on Protected Areas, see https://www.protectedplanet.net/en/thematic-areas/wdpa?tab=WDPA.

growth index, respectively. There also appears to be a negative correlation between these two variations, suggesting that Jevon's paradox holds true.

3.2 Empirical specification

We denote cells by i and years by t. Our first prediction is that the link between fertilizer price growth and deforestation is ambiguous. We estimate the following specification:

$$-\ln(1-r_{it}) = \beta_1 \ln\left(1+g_{it}^f\right) + \mathbf{X'_{it}}\beta_X + \eta_i + \mu_{St} + \varepsilon_{it}, \tag{19}$$

$\text{Deforest}_{it} = -\ln(1-r_{it})$ is our index of deforestation and Fert. p. $\text{growth}_{it} = \ln\left(1+g_{it}^f\right)$ is our index of fertilizer price growth, both derived from equations (11) and (13). In some specifications, we include a vector $\mathbf{X'_{it}}$ that encompasses a set of control variables (the price growth of the agricultural output, average annual temperature and total annual precipitation). In our baseline estimates, we saturate our model with cell and country-year fixed effects (η_i and μ_{St}, respectively). The inclusion of cell fixed effects controls for any time-invariant cell characteristics that may correlate with both the average deforestation rates and crop prices (such as geography, topography, and soil characteristics). The inclusion of country × year fixed effects accounts for any time-variant country characteristics, such as global trends in overall crop prices, nationwide shocks, or policy changes that may trigger or hamper deforestation. $\varepsilon_{i,t}$ is the error term. Standard errors are clustered by the cell in the baseline, and in our sensitivity analysis, we allow for spatially correlated errors within a larger radius (see Table A 3 in Appendix B). We estimate the model using an Ordinary Least Square estimator. Finally, to test predictions #2 and #3, we estimate equation (19) augmented with interaction terms between Fert. price $\text{growth}_{i,t}$ and cell-specific characteristics, e.g. market potential and the share of the cell covered by a protected area (as a proxy of the cost of clearing land).

4 Results

4.1 Agricultural productivity and deforestation in the tropics

Table 2 displays our baseline results. Across tropical regions, we find that cell-specific changes in fertilizer prices and the rate of deforestation are negatively correlated: a decrease in the growth of fertilizer prices corresponds to an increase in tree cover loss. This finding holds when accounting for country×year fixed effects (column 2). Our model (equation 11) highlights that the growth of agricultural output prices is also a significant driver of deforestation. In column 3, where we include the growth of the agricultural output prices, several key results emerge. Firstly, the coefficient of our variable of interest remains largely unchanged. Secondly, we find a positive correlation between the growth of agricultural output prices and deforestation, albeit with a much weaker magnitude compared to fertilizer price growth. Lastly, the magnitude of the effect of fertilizer price growth is sizeable: a one standard deviation decrease in (ln) fertilizer price growth is associated with a 0.26 standard deviation increase in deforestation. This effect is more than ten times larger than the effect of a one standard deviation increase in the (ln) growth of output prices, which results in a 0.02 standard deviation increase in deforestation.

Between 2001 and 2022, fertilizer and output prices increased respectively by an average of 9.7% and 3%, respectively (Table 1). Our estimates in Table 2 indicate that this increase in fertilizer prices resulted in less deforestation, whereas the increase in output prices led to more deforestation over the period. Indeed, in a scenario without any variations in fertilizer prices, deforestation would have been 57% higher (with an annual deforestation rate of 1.1% instead of 0.7%), amounting to an additional 146 millions hectares of deforestation over our study period, or 6.6 millions hectares per year. Conversely, without any change in output prices, deforestation would have been only 3% lower (with an annual deforestation rate of 0.68% instead of 0.7%), representing a reduction of 7.6 million hectares of tree cover loss over the study period.

Interpreting this result through the lens of our model, it suggests that farmers' production is typically not constrained by their market potential. Therefore, a decrease in fertilizer prices generally incentives farmers to expand their farmland by clearing more forested land. In other words, this finding supports the Jevons' paradox in the context of fertilizer price growth and deforestation dynamics in the tropics since 2000, while it does not support Borlaug's hypothesis.

From columns 4 to 7, we conduct several sensitivity tests. First, deforestation in Brazil is predominantly driven by cattle farming, whereas crop farming is more prevalent in other countries (Assunção et al., 2020; Branthomme et al., 2023; Souza-Rodrigues, 2019). Consequently, deforestation in Brazil is expected to be less less sensitive to changes in fertilizer prices than most other countries. When excluding Brazil from our sample (which constitutes 20% of all observations), our main effect remains robust and the magnitude of the effect slightly increases. Second, we address concerns that our findings may be driven solely by countries that are major fertilizer producers. To test this, we exclude cells in the tropics belonging to the largest fertilizer-producing countries (China, India, Indonesia, and USA).[16] The effect size remains unchanged (column 5). Regarding the granularity of the analysis, we exclude outliers, which are defined using the estimates from column (2). We exclude all observations with residuals greater than one quarter of the standard error (7.5% of our sample), yet our results remain consistent (column 6). Finally, including both cell-specific average annual temperature and total annual precipitation does not alter the magnitude of our observed effect (column 7). Additional sensitivity tests are presented in Section 4.4 and in Appendix B.

4.2 The role of market potential

The second prediction of our theoretical model posits that the effect of fertilizer price growth on deforestation varies with the the market potential of the cell. To test this, we augment equation (19) with an interaction between cell-specific fertilizer price growth and our measure of market potential (Table 3). Although not explicitly reported, output price growth is also interacted with our market potential measure.

Consistent with prediction 2, our findings suggest that the effect of fertilizer price changes depends on

[16]see Hernandez and Torero (2013).

Table 2: Baseline Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.:				Deforest			
Sample	full	full	full	w/o Brazil	w/o Top fert. prod.	w/o outliers	full
Fert. price growth	–0.068***	–0.065***	–0.061***	–0.073***	–0.069***	–0.009***	–0.063***
	(0.016)	(0.015)	(0.015)	(0.019)	(0.017)	(0.001)	(0.015)
Output price growth			0.008***	0.012***	0.009***	0.001***	0.008***
			(0.002)	(0.003)	(0.002)	(0.000)	(0.002)
Rainfall							–0.001***
							(0.000)
Temperature							0.002***
							(0.001)
Obs.	300694	300694	300694	240612	260280	267515	292950
Mean Defor.	0.008	0.008	0.008	0.008	0.008	0.004	0.008
Cell FE	yes	yes	yes	yes	yes	yes	yes
Country×Year FE	no	yes	yes	yes	yes	yes	yes
Year FE	yes	no	no	no	no	no	no
Effect of +1 S.D.							
Fert. price growth	-0.015	-0.014	-0.014	-0.016	-0.015	-0.002	-0.014
Output price growth			0.001	0.001	0.001	0.000	0.001

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Standard errors clustered by cell in parentheses. Deforest is our index of deforestation computed as minus the log of one minus the deforestation rate (loss over forest cover), Fert. price growth is the log of one plus the current period fertilizer price growth, and Output price growth is the log of one plus the current period fertilizer price growth. In column (4) we exclude Brazil from our sample. In column (5), top 5 producer countries of the main fertilizer types (Hernandez & Torero, 2013) are dropped: China, India, Indonesia, and USA belong to these countries and contain cells in the tropics. In column (6), we exclude from our sample all the observations with a residual greater than one quarter the standard error (using the estimates from column (2)). * significant at 10%, ** significant at 5%, *** significant at 1%. Standard errors clustered at the cell level the level of (time-invariant) market potential of the cell. Specifically, higher market potential strengthens the impact of fertilizer prices. To rule out the alternative explanation that market potential effects are driven solely by the cell's level of development, we interact changes in fertilizer prices with the cell-specific average nighttime light intensity in 2000. Our results are barely unchanged (column 2). Furthermore, considering the varying proximity of cells to ports and cities, we compute the average distance from each cell to large, medium, and small ports, and interact these distances with changes in fertilizer prices. For cities, we interact with the cell-specific changes in fertilizer prices with different distances to cities, according to their number of inhabitants ([3k-5k[, [5k-50k[, [50k-100k[, [100k-200k[, [200k- 1 million[, [1 million - 5 million[and [5million and +]). Note that the output price growth is also interacted with these distances. Even with these controls, the interaction effect between cell-specific changes in fertilizer prices and market potential remains negative and statistically significant (column 3). In terms of magnitude, the effects are not negligible. For cells with a low market potential (25th percentile, 7.59), a one standard deviation decrease in fertilizer prices is associated with a 0.24 standard deviation increase in deforestation. Conversely, for cells with a high market potential (seventy fifth percentile, 9.32), a one standard deviation decrease in fertilizer prices leads to a 0.28 standard deviation increase in deforestation, indicating that the effect is 16% larger for cells with high market potential compared to those with low market potential.

Table 3: The role of market potential

	Deforestation		
	(1)	(2)	(3)
Fert. price growth	–0.016	–0.019	–0.005
	(0.022)	(0.026)	(0.041)
× Market potential	–0.005***	–0.005**	–0.007*
	(0.002)	(0.002)	(0.003)
Output price growth	0.008***	0.006***	0.031*
	(0.002)	(0.002)	(0.017)
Obs.	300694	300694	300540
Mean Defor.	0.008	0.008	0.008
Cell FE	yes	yes	yes
Country×year FE	yes	yes	yes
Nighttime light	no	yes	yes
Distance to cities	no	no	yes
Distance to ports	no	no	yes

Note. * significant at 10%; ** significant at 5%; *** significant at 1%. Standard errors clustered by cell in parentheses. Output price growth and corresponding interaction var. included but coef not reported. Deforest is our index of deforestation computed as minus the log of one minus the deforestation rate (loss over forest cover), Fert. price growth is the log of one plus the current period fertilizer price growth, and Output price growth is the log of one plus the current period fertilizer price growth. Market potential is the log of night time lights intensity in 2000 weighted by the inverse of the distance between the cells. * significant at 10%, ** significant at 5%, *** significant at 1%. Standard errors clustered at the cell

4.3 Protected areas

Prediction 3 from our theoretical model stipulates that an increase in the cost of converting land does not affect the relationship between agricultural productivity and deforestation. Protected areas mean higher total clearing costs for those who violate them, due to the fines imposed (Robinson et al., 2010). Consequently, we replicate the specifications displayed in Table 3 by adding an interaction term between the cell-specific changes in fertilizer prices and the presence of protected areas. From columns (1) to (3), our measure encompasses all protected areas included in WDPA dataset. We do not identify any significant effect of protected areas on the relationship between fertilizers price growth and deforestation. The literature explicitly mentions that enforcement of protected areas is an important determinant of their effectiveness. This is why, from columns 4 to 6, we focus only on the least permissive protected areas, corresponding to those with a IUCN classification I and II.[17] Once again, our empirical estimate is consistent with prediction 3, since we do not identify a different effect of agricultural productivity growth on deforestation according to this measure of strength of protected area enforcement (which should theoretically increase the cost of forest clearing).

Table 4: The role of protected areas

	Deforestation					
	(1)	(2)	(3)	(4)	(5)	(6)
Fert. price growth	–0.016	–0.019	–0.005	–0.016	–0.018	–0.004
	(0.022)	(0.026)	(0.041)	(0.022)	(0.026)	(0.041)
× Market potential	–0.005***	–0.005**	–0.007*	–0.005***	–0.005**	–0.007*
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
× Parks	0.001	0.001	0.001			
	(0.001)	(0.001)	(0.001)			
× Parks, cat 1 or 2				0.001	0.001	0.001
				(0.001)	(0.001)	(0.001)
Output price growth	0.008***	0.006**	0.031*	0.008***	0.006***	0.031*
	(0.002)	(0.002)	(0.017)	(0.002)	(0.002)	(0.017)
Obs.	300694	300694	300540	300694	300694	300540
Mean Defor.	0.008	0.008	0.008	0.008	0.008	0.008
Cell FE	yes	yes	yes	yes	yes	yes
Country×year FE	yes	yes	yes	yes	yes	yes
Nighttime light	no	yes	yes	no	yes	yes
Distance to cities	no	no	yes	no	no	yes
Distance to ports	no	no	yes	no	no	yes

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Standard errors clustered by cell in parentheses. Deforest is our index of deforestation computed as minus the log of one minus the deforestation rate (loss over forest cover), Fert. price growth is the log of one plus the current period fertilizer price growth. Output price growth and corresponding interactive variables are included but the coefficients are not reported. * significant at 10%, ** significant at 5%, *** significant at 1%. Standard errors clustered at the cell

[17]Protected Areas of IUCN category I aims at preserving ecosystems in a pristine, undisturbed state with minimal human intervention. In IUCN category II, some sustainable human activities such as recreation and tourism are permitted but they are still prioritizing conservation efforts. In comparison, IUCN categories III to VI represent a spectrum of protected areas with varying management objectives. They emphasize more the promotion of sustainable resource use.

4.4 Sensitivity Analysis

Heterogeneity We found no strong heterogeneity in the main effect between cells with different levels of market potential (see Table 3), part of a protected area or not (Table 4), or geographical location (Tables 3 and 4). In addition, to rule out the possibility of specific years or countries driving our main result, we remove years and countries one by one, and our main point estimate remains remarkably stable (Figures A 1 and A 2).

Dynamic Effects Most of our results suggest little spatial and temporal heterogeneity (see above). Moreover, our theoretical model shows that contemporaneous fertilizer price growth affects deforestation without impacting future deforestation, indicating that there are theoretically no dynamic effects. To confirm that heterogeneous or dynamic effects are not a threat to our conclusions, we use a recent approach that is robust to heterogeneity.

In our baseline specification, our "treatment" refers to the fluctuation in fertilizer price growth, which is a continuous variable. To test whether there are dynamic effects, we compute the estimator proposed by de Chaisemartin and D'Haultfœuille (2024). For this, we slightly modify the definition of our price index. The design requires that at least two groups of cells share the same treatment during the initial period (2001) but diverge in subsequent years of treatment. Specifically, fertilizer price growth in certain cells must become non-null at different points in time. Analysis of the trends in nitrogen, phosphorus, and potassium prices on the international market (Figure A 3 in Appendix B) indicates relative stability in 2001 and 2002, with growth rates of less than 5%. Nitrogen prices experienced an initial spike in 2003, followed by spikes in potassium and phosphorus prices in subsequent years. We leverage these (three) staggered spikes to estimate the dynamic impact of fertilizer price growth on deforestation.

Doing so, we disregard fertilizer price growth rates below 5% by setting them to zero. Additionally, we only consider the most suitable crop in each cell and omit less critical nutrients for this crop. Specifically, we exclude nitrogen, phosphorus, or potassium when their respective shares in Table A 4 are less than one third, recalculating the shares accordingly. With these assumptions, we can employ the dynamic estimator as design restriction 1 in de Chaisemartin and D'Haultfœuille (2024) holds true in our dataset. Using this modified measure of fertilizer price growth (the natural logarithm of one plus the growth rate, in line with theory), we estimate the following equation:

$$-\ln(1 - r_{i\tau}) = \sum_{t=-1, t\neq 0}^{2} \beta_1^{t-1} \ln\left(1 + \tilde{g}^f_{i\tau+t-1}\right) + \mathbf{X}'_{\mathbf{i}\tau}\beta_X + \eta_i + \mu_\tau + \varepsilon_{i\tau}, \tag{20}$$

where $\tilde{g}^f_{i\tau+t-1}$ represents the fertilizer price growth at time $\tau + t - 1$ for the main nutrients of the most suitable crop in cell i. We assess the impact of fertilizer price growth up to two years following changes in price growth, as well as a placebo effect two years prior to the treatment (with $t = 0$, the year before the treatment, as the reference point). To discern between the effects attributed to changes in the fertilizer price index and those resulting from modifications to the estimator, we also re-estimate our baseline model using the adjusted fertilizer price index.

Table 5: Dynamics effects vs TWFE

	(1)	(2)	(3)	(4)
Dep. Var.:		Deforest		
Estimator	TWFE	dCDH (2024)	TWFE	dCDH (2024)
Fert. price growth$_{\tau}$	.000	-.003***	.000	-.003***
	[-.000,.001]	[-.005,-.002]	[-.000,.001]	[-.005,-.002]
Fert. price growth$_{\tau-2}$		.000		.000
		[-.001,.002]		[-.001,.001]
Fert. price growth$_{\tau+1}$		.000		.000
		[-.001,.002]		[-.001,.002]
Cell FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Weather controls	no	no	yes	yes
Effect of +1 S.D.				
Fert. price growth$_{\tau}$	.000	-.001	.000	-.001

Notes: 95% confidence intervals in brackets. Deforest is our index of deforestation computed as minus the log of one minus the deforestation rate (loss over forest cover), Fert. price growth is the log of one plus the current period fertilizer price growth. Weather controls include rainfall and temperature. All regressions include Output price growth as a control variable.

Our estimates are presented in Table 5. In columns (1) and (2), we solely incorporate growth in output prices as control variables. Employing the Two-Way-Fixed Effects (TWFE) estimator akin to our baseline, we observe a minimal and statistically insignificant impact of the adjusted fertilizer price growth measure. This outcome is somewhat expected, considering that the modified measure is significantly simpler compared to our original approach. Notably, it only considers the most suitable crop in each cell and the primary nutrients for that particular crop, whereas our original measure encompasses all suitable crops and their corresponding nutrient requirements. Using the dynamic DID estimator proposed by de Chaisemartin and D'Haultfœuille (2024) to estimate the impact of continuous treatments, we detect a negative effect of the adjusted fertilizer price growth measure on deforestation (column 2). However, this effect appears considerably weaker than in our baseline estimates, presumably due to the coarse nature of our modified measure. In columns (3) and (4), we re-estimate the same specifications as in columns (1) and (2), augmented with weather controls. The inclusion of these additional controls does not alter our findings. Figure 1 depicts the findings derived from column (4), revealing that the impact of fertilizer price growth is negative one year following the fertilizer price growth shock but the effect does not persist. Importantly, there is no anticipation of the effect, and there are no discernible differences between the treated and control cells prior to the fertilizer price shock.

These results largely validate our qualitative observations. Firstly, they indicate that the effect of fertilizer price growth is contemporaneous, aligning with the predictions of our theoretical model. Secondly, the negative impact of fertilizer price growth on deforestation suggests the presence of Jevons's paradox rather than Borlaug's hypothesis.

Other sensitivity tests. We show that our estimates are robust when changing the canopy threshold to defined forest from 25% to 10% or 50% (Table A 2). Secondly, recognizing the spatial correlation

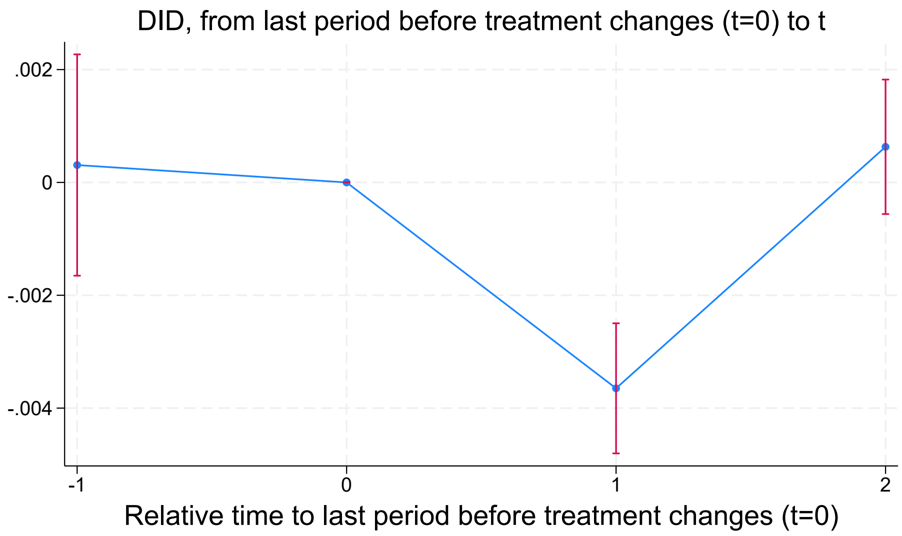

Figure 1: Dynamic effects (de Chaisemartin & D'Haultfœuille, 2024)

Note. Point estimate and confidence interval from Table 5 column (4).

between crop suitability and the autocorrelation of fertilizer prices, we allow the error terms to exhibit infinite autocorrelation and spatial correlation up to various distances (ranging from 100km to 500km). We implement this by computing Conley (1999) standard errors (see Table A 3 in the Appendix). Notably, our estimates of the fertilizer price growth effect remain highly precise. However, we observe a loss of precision in our estimates of the output price growth effect as we increase the spatial radius.

5 Concluding Remarks

Deforestation has significant global social welfare implications, often driven by rational economic decisions made by farmers facing trade-offs. In this paper, we contribute to understanding these decisions, focusing particularly on the debated relationship between agricultural productivity and deforestation, which has yielded mixed empirical findings.

We develop a dynamic model of agricultural production that incorporates deforestation and derive predictions regarding how farmers respond to changes in input and output prices, considering factors such as market potential and forest protection policies. Our model reveals theoretical ambiguity in how deforestation reacts to price growth changes and highlights mispecifications in previous empirical studies concerning this relationship. Empirically, we test our predictions on a large scale across the entire tropical band. We find that decreases in agricultural productivity, represented by exogenous fertilizer price growth between 2000 and 2022, led to lower deforestation rates compared to scenarios without this fertilizer price growth. This elasticity varies with the farmers' market potential but is unaffected by the presence of protected areas.

Importantly, our analysis shows that fertilizer price growth exerts a larger impact on deforestation than output price growth. This finding underscores the policy implications: demand-side policies, such as those affecting food demand, have limited potential to mitigate deforestation compared to supply-side policies. Moreover, global agricultural subsidies, exceeding $635 billion annually, making agriculture the world's most distorted sector (Panagariya, 2005), significantly influence fertilizer prices and usage, thereby impacting deforestation trends. Decreasing these subsidies, at least in areas with high market potential, could yield beneficial outcomes for forest conservation.

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Appendix

A Theory

Since our deforestation data (Hansen et al., 2013) focuses on forest loss rather than forest cover or reforestation, our analysis predominantly centers on deforestation rather than changes in forest cover in both theory and empiric. Our model also allows us to explore the relationship between fertilizer prices and forest cover. As discussed in the theory section, this relationship hinges on whether the constraint imposed by market potential is binding. When the market potential constraint is not binding, using equation (10) and $F_t = \frac{1}{\epsilon} A_t^{-\epsilon}$, we find that the optimal forest cover level F_t^* is characterized by:

$$\ln(F_t^*) = \beta_1^F \ln(p_t^f) + \beta_2^F \ln(p_t^o) + \eta_t, \tag{21}$$

where $\beta_1^F = \frac{\epsilon\gamma}{1-\alpha-\gamma} > 0$, $\beta_2^F = -\frac{\epsilon}{1-\alpha-\gamma} < 0$, and $\eta_t = -ln(\epsilon) - \epsilon\Psi_t$.

In this case, a decrease in fertilizer prices or an increase in output prices lead to a decrease in forest cover.

When the market potential constraint is binding, we obtain, using equation 12:

$$\ln(F_t^*) = \beta_0^F + \beta_1^F \ln(p_t^f), \tag{22}$$

where $\beta_1^F = -\frac{\epsilon\gamma}{\alpha+\gamma} < 0$ and $\beta_0^F = \frac{1}{\alpha+\gamma}\ln(\bar{y}) + \frac{\gamma}{\alpha+\gamma}\ln(\frac{\alpha}{\gamma c_l})$.

Here, the expectation of the parameter of interest is $E\left[\beta_1^F\right] = G(\bar{y})\frac{\epsilon\gamma}{1-\alpha-\gamma} - (1-G(\bar{y}))\frac{\epsilon\gamma}{\alpha+\gamma}$. The sign of the relationship between fertilizer prices and forest cover is thus ambiguous. Intuitively, one would expect tha that it is opposite to the sign of the effect of fertilizer price growth on deforestation, $E[\beta_1]$. But it is not necessarily the case since $E[\beta_1] \geq 0 \equiv G(\bar{y}) \leq \frac{1}{2}$ while $E\left[\beta_1^F\right] \geq 0 \equiv G(\bar{y}) \geq 1-\alpha-\gamma$. As previously mentioned, the Hansen data are not well-suited for studying forest cover. However, it is feasible to build an annual measure of forest cover by subtracting cumulative forest losses from the forest cover in 2000. Using this measure and our data, our estimates again suggest a trend aligned with Jevon's paradox: higher fertilizer prices are associated with higher level of forest cover (see Appendix B).

B Figures and Tables

Table A 1: Forest cover

	(1)	(2)	(3)	(4)	(5)	(6)	(6)
Dep. Var.:				Forest cover			
Sample	full	full	full	w/o Brazil	w/o Top fert. prod.	w/o outliers	full
(log-) Fert. Price	44.102***	34.836***	20.496***	19.765***	28.255***	18.683***	21.626***
	(1.571)	(2.133)	(2.088)	(2.124)	(2.274)	(0.608)	(2.185)
(log-) Output Price			–14.566***	–17.930***	–11.993***	–0.629***	–15.304***
			(0.802)	(0.903)	(0.813)	(0.111)	(0.816)
Rainfall							0.137
							(0.130)
Temperature							0.489***
							(0.160)
Obs.	300694	300694	300694	240612	260280	146264	292950
Mean Forest cover	139.601	139.601	139.601	130.096	145.202	116.488	143.090
Cell FE	yes	yes	yes	yes	yes	yes	yes
Country×Year FE	no	yes	yes	yes	yes	yes	yes
Year FE	yes	no	no	no	no	no	no
Effect of +1 S.D.							
Fert. price	16.318	12.889	7.584	7.313	10.454	6.913	8.002
Output price			-2.841	-3.496	-2.339	-0.123	-2.984

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Standard errors clustered by cell in parentheses. Forest cover is our measure of forest cover (in thousands of hectares) computed as the initial forest cover in 2000 minus the sum of the past forest losses, (log-) Fert. price is the log of the current period fertilizer price, and (log-) Output price is the log of the current period fertilizer price. In column (4) we exclude Brazil from our sample. In column (5), top 5 producer countries of the main fertilizer types (Hernandez & Torero, 2013) are dropped: China, India, Indonesia, and USA belong to these countries and contain cells in the tropics. In column (6), we exclude from our sample all the observations with a residual greater than one quarter the standard error (using the estimates from column (2)).

Appendix 2.1 Dropping each year one by one

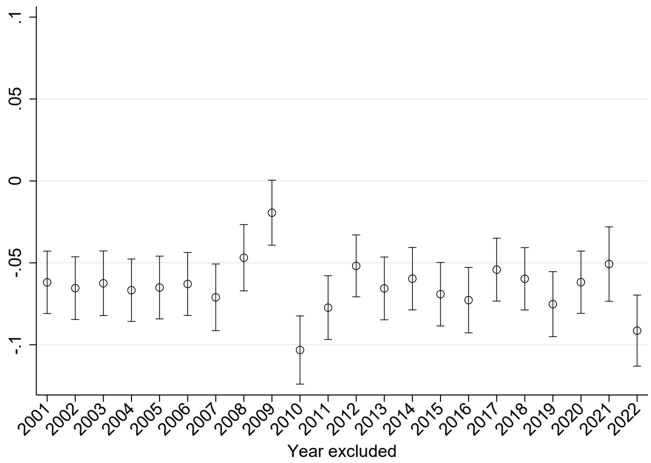

Figure A 1: Dropping years

Note. Each point estimate and confidence interval come from a regression using the same specification as in Table 2 column (2) and the same sample, but without the year shown on the x-axis.

As shown in Figure A 1 , the results are not sensitive to the exclusion of each year one by one, except for 2009 and 2010. Not surprisingly, 2009 is the year in which fertilizer prices soared. 2010 is the year just after the peak, when fertilizer prices returned to more normal levels. Excluding the years 2009 and 2010, our estimate is very close to our estimates in Table 2, equal to -.067 and significant at the 99% confidence level.

Appendix 2.2 Dropping countries

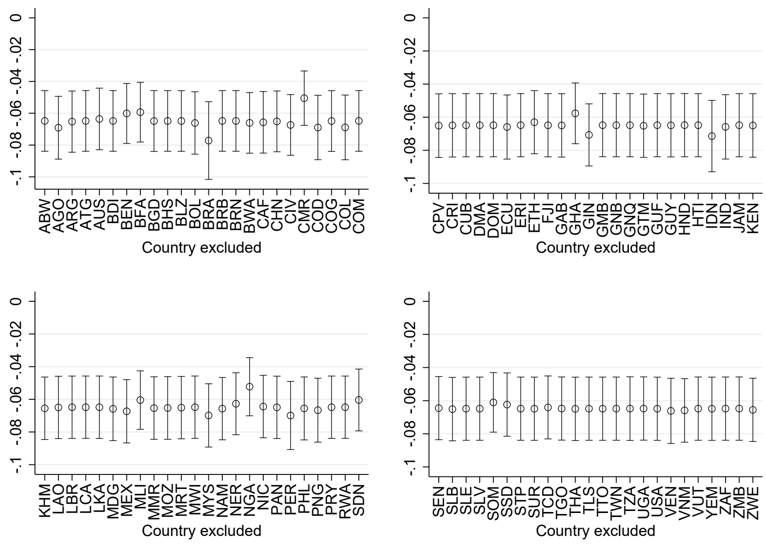

Figure A 2: Dropping each country one by one

NOTE. Each point estimate and confidence interval come from a regression using the same specification as in Table 2 column (2) and the same sample, but without the country whose iso3 code is shown on the x-axis.

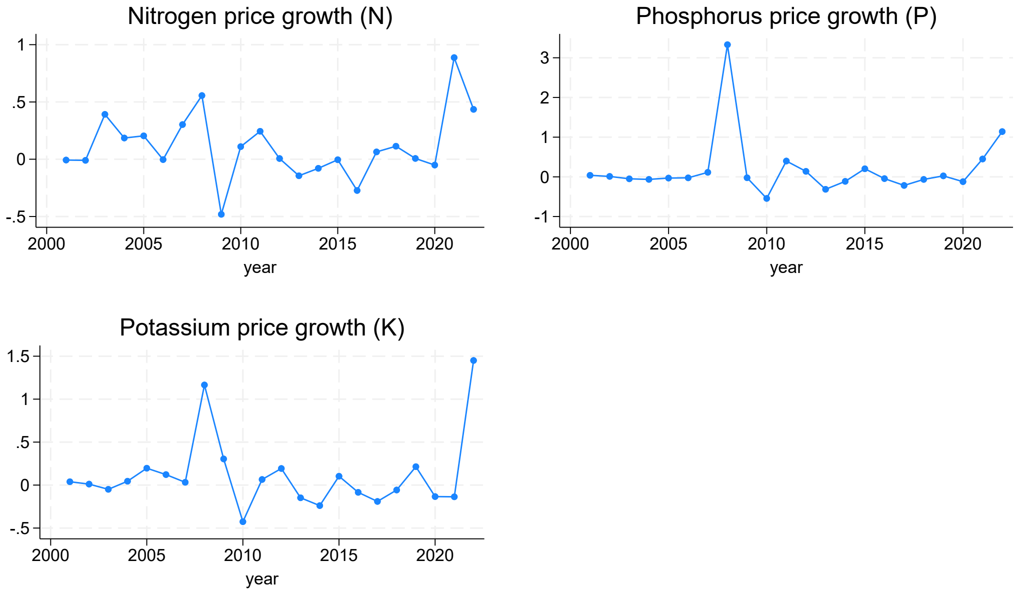

Figure A 3: Evolution of real international prices growth of nitrogen, phosphorus, and potassium (2001-2022).

Note. Data on the real international market prices of each nutrient come from the World Bank Commodities Dataset, see https://databank.worldbank.org/databases/commodity-price-data.

Table A 2: Various canopy thresholds

	(1)	(2)	(3)
Dep. Var.:		Deforest	
Canopy threshold	25%	10%	50%
Fert. price growth	–0.061***	–0.007***	–0.075***
	(0.015)	(0.002)	(0.022)
Output price growth	0.008***	0.001	0.021***
	(0.002)	(0.001)	(0.003)
Obs.	300694	300683	290137
Mean defor. rate	0.007	0.005	0.010
Cell FE	yes	yes	yes
Country×Year FE	yes	yes	yes

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Standard errors clustered by cell in parentheses. Deforest is our index of deforestation computed as minus the log of one minus the deforestation rate (loss over forest cover), Fert. price growth is the log of one plus the current period fertilizer price growth, and Output price growth is the log of one plus the current period fertilizer price growth. We reproduce Table 2 column (3) estimates in column (1). In columns (2) and (3), we use alternative canopy thresholds. The canopy threshold is the minimal percentage of forest cover in 2000 so that a pixel is considered as forested in 2000.

Table A 3: Conley standard errors

	(1)	(2)	(3)	(4)	(5)
Dep. Var.:			Deforest		
Radius	100km	200km	300km	400km	500km
Fert. price growth	–0.061***	–0.061***	–0.061***	–0.061**	–0.061**
	(0.020)	(0.022)	(0.022)	(0.025)	(0.028)
Output price growth	0.008***	0.008**	0.008**	0.008**	0.008*
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Obs.	300694	300694	300694	300694	300694
Mean Deforest.	0.009	0.009	0.009	0.009	0.009
Cell FE	yes	yes	yes	yes	yes
Country×Year FE	yes	yes	yes	yes	yes

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Conley (1999) standard errors in parentheses. Deforest is our index of deforestation computed as minus the log of one minus the deforestation rate (loss over forest cover), Fert. price growth is the log of one plus the current period fertilizer price growth, and Output price growth is the log of one plus the current period fertilizer price growth. We use the specification from Table 2 column (3). We compute Conley (1999) standard errors allowing for infinite temporal and a radius of 100km to 500km.

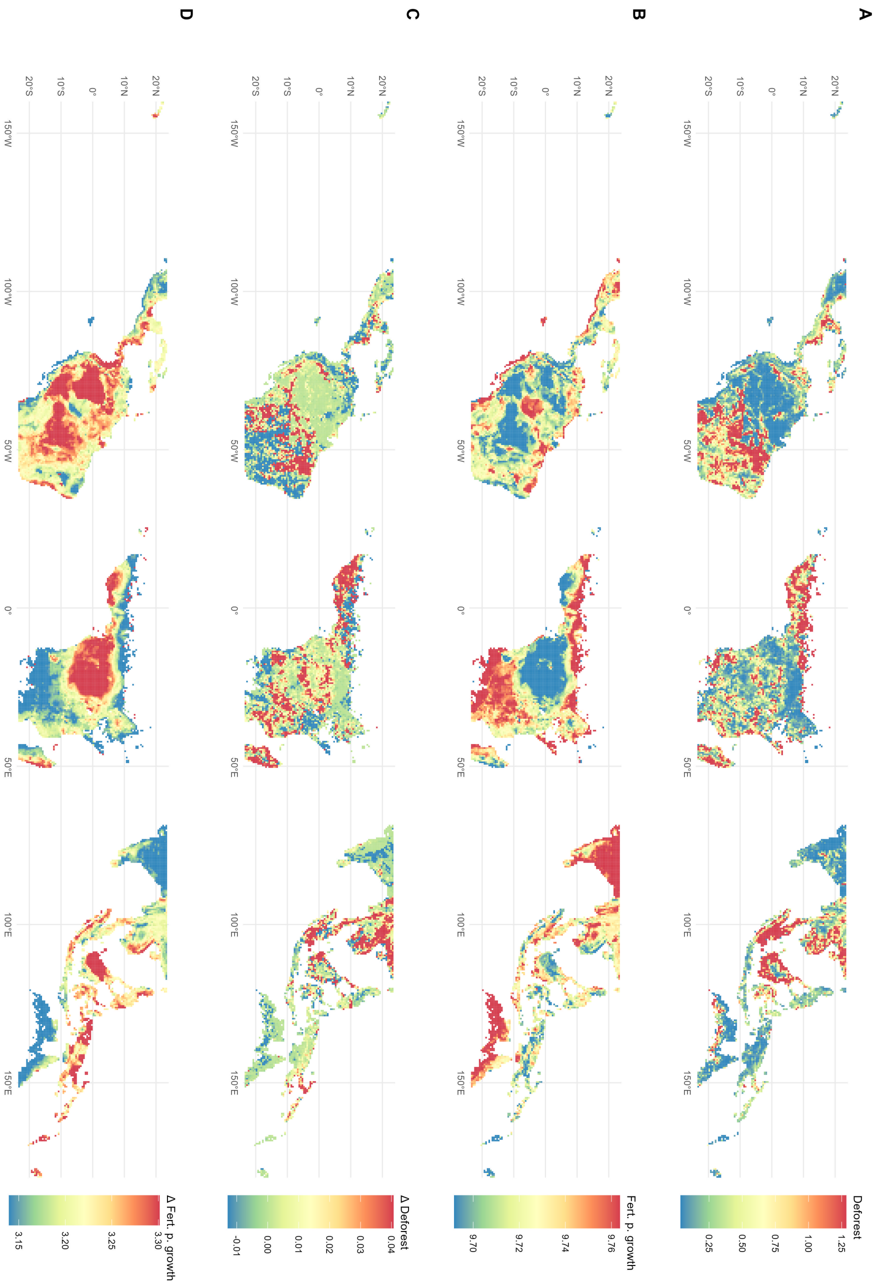

Figure A 4: Descriptive statistics maps

Note. Panel A shows the average of our main outcome deforestation variable for each 0.5° cell (Deforest, see Table 1). Panel B shows the average of fertilizer price growth for each 0.5° cell (Fert. price growth, see Table 1). Panel C and Panel D show the year to year variations of the variables shown in Panel A and B for each 0.5° cell, respectively. Forest loss data come from Hansen et al. (2013), see https://www.globalforestwatch.org. The fertilizer price index is computed as explained in Section 3.1.

Table A 4: Nutrients shares by crop

Crop name	N	P	K
Alfalfa	.46	.11	.44
Barley	.58	.23	.19
Buckwheat	.64	.19	.17
Cabbage	.46	.11	.43
Chickpea	.56	.28	.16
Citrus	.41	.08	.51
Cotton	.49	.22	.29
Cowpea	.64	.17	.19
Dryland rice	.56	.29	.15
Drypea	.64	.17	.19
Flax	.65	.19	.16
Green gram	.64	.17	.19
Ground nut	.71	.11	.17
Maize	.48	.16	.36
Millet	.64	.18	.18
Oat	.62	.23	.15
Pigeon pea	.56	.28	.16
Rapeseed	.57	.29	.14
Reed grass	.43	.19	.38
Rice	.56	.29	.15
Rye	.65	.21	.14
Sorghum	.5	.3	.21
Soybean	.63	.14	.23
Sugarcane	.29	.2	.51
Sugarbeet	.28	.16	.55
Sunflower	.59	.21	.2
Sweet potato	.3	.13	.57
Switchgrass	.24	.13	.63
Tobacco	.35	.09	.56
Tomato	.28	.11	.62
Wheat	.58	.26	.15
White potato	.27	.14	.59

Note: This table shows nutrients uptake share for each crop, computed thanks to the quantity of nutrient removed from the field at crop harvest, in kg/ha. For instance, the third raw second column value is $q^N_{Barley} = x^N_{Barley}/(x^N_{Barley} + x^P_{Barley} + x^K_{Barley}) = 0.11$, where x^N_{Barley}, x^P_{Barley} and x^K_{Barley} are the quantities of N, P205 and K20 removed from the field when barley is harvested, in kg/ha. The data comes from the International Plant Nutrition Institute(IPNI). These represent what IPNI scientists believe to be the best estimates of typical values to date of nutrient uptake for different crops grown in different countries of the world. See http://www.ipni.net/article/IPNI-3296.